# Does Corporate R&D Investment Affect Firm Environmental Performance? Evidence from G-6 Countries

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## Abstract

The rate of climate change due to global warming has become a substantial concern and appeared as a real-world phenomenon in the recent years. However, it is imperative to know how business enterprises alter such concern. Recent studies involve a variety of firm-level factors to create a robust link between business enterprises' environmental and financial performance. However, little is known regarding the role of research and development (R&D) investment on firms' environmental performance. Using a firm-level data for the period 2004 – 2016 from G-6 countries, this study empirically investigates how R&D investment affects the firm environmental performance measured by energy and carbon emissions intensities. We find that R&D investment improves the firm's environmental performance consistent with the theoretical argument of natural resource-based view (NRBV). Our findings are robust to alternative econometric specifications, alternative variable specifications, and sub-samples. Our findings offer novel insights to the policymakers, business managers, and regulators.



***Keywords*: Sustainability, carbon emissions, energy intensity, corporate R&D investment**
***JEL Classification:* F21, G15, O32, P28**

# 1 Introduction

Climate change has emerged as a priority agenda both in developing and developed economies. In December 2015, 195 countries approved and adopted the first-ever legally binding global climate agreement at the Paris climate conference (COP21). The agreement focuses on an action plan to set the whole world to undertake various measures on climate change by restraining the rise of global temperature to less than 2°C. Although Washington has proclaimed its intention to withdraw the US from the Paris Agreement, all the major carbon-emitting countries, including China, EU, Germany, India, Japan, and Russia, have expressed their strong intention to maintain their commitments. All the signatories of the agreement agreed that Greenhouse Gas (GHGs), particularly carbon emissions, should be decreased to mitigate global warming risks. Therefore, high carbon emitting countries, such as Germany, Japan, and the US are under immense global pressure to reduce carbon emissions significantly arising from fossil fuel energy consumption (Randers, 2012; Lee, 2012).

Business enterprises play a significant role in increased carbon emissions due to their energy consumption for producing goods and services. With the ever-increasing environmental pressures from the government and policymakers, business enterprises look for means to minimise their environmental impact through raising energy efficiencies, reducing pollution, and encouraging reuse and recycling (Porter and Reinhardt, 2007). However, investing in environmental management increases costs without resulting in financial benefits. Therefore, the vital question corporate managers are now facing is how to minimise environmental impacts without reducing firm performance (Lee and Min, 2014). Recently, management literature emphasizes the idea of 'win-win' environmental policies that investment in environmental strategies will benefit both environmental and economic performance. In this connection, corporate research and development (R&D) investment plays a substantial role in reducing environmental impacts without compromising business economic return.

The natural resource-based view (NRBV) postulates that a firm can achieve sustainable competitive advantages through the allocation of its resources and capabilities in environmental-friendly business activities. In this line, corporate R&D, a firm's investment of resources in the development of new products or services, processes and technologies, may stimulate business performance and minimise environmental impacts. Corporate R&D plays two key roles in reducing environmental impacts without compromising business return. First, it helps to attain technological development, which intensifies production speed without the demand for increased energy. For example, the output of corporate R&D is often involved with the invention of better equipment and machinery that enhances the production efficiency with minimal energy consumption. Thus, corporate R&D investment results in the reduction of energy intensity (energy/output ratio). Second, corporate R&D fosters the development and deployment of new and improved clean energy technologies that play a central role in the transition towards cleaner sources of energy in the energy system. Moreover, new technologies enable a shift in the trajectory of the energy consumption with improved energy efficiency. Thus, the nourishment of corporate R&D activities can be a significant tool to improve environmental performance particularly in reducing energy and carbon emission intensities of firms along with their business growth.

While corporate R&D is expected to have a significant impact on reducing energy and carbon intensities, a little is known on this issue. One of the potential reasons for lacking study in this area may be the unavailability of firm-level data. Therefore, this study aims to contribute in this area of literature considering the G-6[1] (Canada, France, Germany, Japan, the UK, and the USA) countries as a sample. We choose the sample from G-6 for two reasons. First, G-6 countries have notable investment in R&D, renewable energy technologies (ICTs) and other

[1] We initially intended to consider G-7 countries as a sample for this study. However, due to the lack of data in Italy, we had to restrict our analysis to G-6 countries.

infrastructures that are needed for reducing carbon emissions. For example, according to the OECD (2018), G-6 countries, such as Canada (1.60%), France (2.23%), Germany (2.93%), Japan (3.14%), UK (1.70%) and the USA (2.74%), spend a significant proportion of their GDP in R&D activities. In terms of total dollar spending, G-6 were also among the leading positions in 2016. In terms of firm-level R&D investment, firms in the G-6 countries such as Amazon, Toyota, Apple and Johnson & Johnson are the pioneers in corporate R&D investment (OECD, 2016). Such R&D investment usually promotes large volumes of technology innovation for raising energy efficiency and clean energy production which may have a substantial influence on reducing carbon emissions. Therefore, it is essential to investigate the relationship among corporate R&D investment, energy, and carbon intensities in G-6 countries. Second, all of the G-6 countries are members of the Paris Agreement and fully committed to the transition to climate-resilient, low-carbon and resource-efficient economies. As mentioned earlier, even after the USA's intention to withdraw from this agreement, other member countries are fully determined to strengthen the financial, technological and capacity building supports. Thus, as a matter of practicality and relevance, the sample is restricted to six developed economies who are pioneers in R&D investment and environmental management.

Our study answers the question employing firm-level data for a sample of 1,350 firms for the period of 2004–2016, amounting to 9,792 firm-year observations. We find that R&D investment negatively affects the energy and carbon emissions intensities suggesting that R&D investment leads to efficient energy consumption, thus lower carbon emissions. These results are robust to alternative variable specifications, sub-samples, lagged or dynamic effects, and alternative econometric specifications. Further, our study faces a challenge of omitted variables bias that arises due to the motivation of managers in R&D investment to improve and create new technologies in response to regulatory pressure (e.g., the Paris agreement) leading to a better environmental performance. Another reason may be that a shortage of funds affected by business cycle leads to poor environmental performance and owing to economic differences among countries. Therefore, our independent variables may suffer from a bias and may not be systematically associated with our dependent variables. We address this concern implementing three strategies including country-level variables, propensity score matching (PSM), and an instrumental variable (IV) approach (two-stage least squares 2SLS) (Harford et al., 2012). Our results remain qualitatively consistent with main findings across these strategies.

Our study contributes to the existing body of knowledge in the following ways. First, we empirically investigate the relationship between corporate R&D investment, energy and carbon emissions intensities using firm-level data and provide further empirical evidence in the sustainability literature. While the determinants of energy consumption and carbon emissions have been a popular topic for researchers at macro-level, a study using firm-level data is particularly scarce. The macro-level investigation offers the general trend of emissions but limited to providing direct policy guidelines to decrease the carbon emissions (Dowell et al., 2000). In considering the significance of this issue, this paper offers micro-level analysis of energy and carbon emissions intensities. Furthermore, we test the dynamic relationship between corporate R&D investment and energy and carbon emissions intensities. Second, this paper offers insights to policymakers and corporate managers from the case of the G-6 countries, which are among the largest industries in the world economy. These countries have experienced a substantial change in environmental policies, changing from a passive position to an active one. A prime example of this active position is the reaffirmation of commitment to the Paris accord by the world G-6 leaders to reducing carbon emissions. As a result, manufacturing firms in G-6 are expected to have a different business environment compared to firms from the Anglo-American economies, where policies toward climate change are expected to remain passive. Third and finally, along with policy guidelines, the empirical findings of this study support the fundamental theoretical argument of the NRBV that the employment of firm's scarce resources and capabilities on environmental activities helps a firm to achieve sustainable competitiveness by reducing energy uses and carbon emissions.

The remainder of the paper is structured as follows. Section 2 focuses on both the theoretical and empirical literature review and hypothesis development. Section 3 highlights the research design while Section 4 focuses on the empirical results and discussions. Section 5 concludes the paper and provides future research directions.

## 2 Literature Review and Hypothesis Development

The resource-based view (RBV) of the firm is often used as a theoretical paradigm for achieving competitive advantage. The proponents of RBV theory argue that the competitive advantage of a firm largely depends on the use of firm's valuable tangible and intangible properties and resources. However, the RBV ignores the relationship between firm and its natural environment. While firm competitiveness in eco-innovation and environmental sustainability might have not been important before the 1990s, the importance of sustainable advantage has become imperative in the modern age since firm faces enormous environmental pressures from marketplace and regulatory authorities (Cheng et al., 2014). To respond to such pressure, Hart (2005) advocated the natural resource-based view (NRBV) which proposes that a firm can enjoy sustainable competitiveness by using its resources and capabilities for long-term environmental-friendly products, processes and technologies rather than short-term profits and benefits. Thus, the NRBV provides the holistic view on the link among firm's resources, competence and performance, which comprise the foundation for sustainable competitiveness.

Sustainable competitiveness can be achieved through R&D investment, that is, allocation of firm's resources and capabilities for new products/services, processes and technological developments which increase firm's operational efficiency on one the hand and reduce environmental adversities on the other. Therefore, a group of theoretical literature in the field of sustainability research claims that proactive environmental policies including R&D investment may create a win-win situation by enhancing firm's financial and environmental performance. For example, Esty and Porter (1998) claim that a firm can achieve better financial performance by being a first mover in introducing environmental-friendly products and services. Hart (1997) suggests that managers generally underestimate the economic return from environmental investment. The volunteer environmental activities of firms often provide un-foreseen financial returns. Likewise, King and Lenox (2002) argue that when a firm invests in R&D activities, they lead to improved productivity and reduced environmental costs. In a similar vein, McWilliams and Siegel (2001) point out that incurring costs in environmental activities positively affects firm's reputation to the stakeholders which boost the value of the firm to a greater extent. Therefore, an environmentally proactive firm may enjoy both financial and environmental returns simultaneously from its investment in environmentally friendly activities.

As mentioned earlier, although the empirical literature is scarce, particularly on the relationship among corporate R&D, energy consumption, and carbon emissions, a wide range of literature is available on the relationship between R&D intensity and firm's environmental management. For instance, a strand of literature (e.g., McWilliams and Siegel, 2000; Rothenberg and Zyglidopolous, 2007; Hull and Ruthenberg, 2008; Padgett and Galan, 2010) investigates the relationship between R&D intensity and corporate social responsibility (CSR) by considering firm's environmental activities as a part of CSR. McWilliams and Siegel (2000) find a positive and significant relationship between R&D intensity and CSR activities. Similarly, Rothenberg and Zyglidopolous (2007) have reported that R&D intensive firms are more likely to have high CSR. The same finding is also confirmed by Hull and Ruthenberg (2008). However, Padgett and Galan (2010) provide different empirical evidence in this regard.

The result of their study shows that R&D intensity has significant relationship with CSR in manufacturing industries, while a non-significant result is observed in non-manufacturing industries. Some studies focus on the relationship between R&D and sustainability practices more specifically. For instance, Arora and Cason (1996) provide the empirical evidence that firm's expenditure in R&D has a positive impact on environmental management. Chakrabarty and Wang (2012) examine the similar issue for multinational corporations (MNCs). Employing longitudinal panel data from 1989 to 2009, the study provides evidence that the MNCs which have higher R&D are more likely to implement better sustainability practices. Recently, Jiang et al. (2014) find that R&D intensity helps to reduce industrial soot emissions significantly in Chinese manufacturing firms.

On the particular topic of R&D, energy and carbon emissions intensities, a few researchers analytically argue that investment in R&D promotes modern and innovative technology and know-how which play a significant role to improve energy performance. For instance, Sagar and Holdren (2002) contend that R&D leads to technological advancement which minimises energy costs and risks. This progress also encompasses energy supplies, raises the efficiency of conversion from crude energy to final end-use forms and improves the quality related to energy services. It also decreases the negative environmental consequences resulting from energy production, supply and consumption. Likewise, Sohag et al. (2015) claim that innovation and advanced technology enables economies to shift from traditional and non-renewable to clean and renewable energy sources. Nevertheless, Yongping (2011) advocates that the degree of the consequence of technological progress is more important because of its link with the energy effectiveness. Hence, technological development and innovation help to decrease energy use that in turn energy use efficiency.

Subsequently, Fisher-Vanden et al. (2004), one of the seminal quantitative studies, examine the factors that influence the energy intensity of China. By using firm-level data covering the period of 1997 to 1997, the study suggests that technological development plays a crucial role in reducing China's energy intensity. In the same vein, Inglesi-Lotz (2017) explores the impact of R&D investment in major global seven economies. By employing country-level panel data, the authors show that R&D investment have considerable effect on improving energy efficient know-how and technology. Nevertheless, a few studies have not found any evidence that public R&D spending reduces energy intensity significantly. For instance, Sagar and Zwaan (2006) investigate how public R&D spending affects national energy intensity and carbon emissions. By using various econometric methodology, the study fails to provide any substantial association between them. Similarly, Greening et al. (2000) argue that if the improved energy efficiency leads to drop the energy price, then the reduced price encourages individuals and business enterprises to consume more energy which ultimately rises energy use and carbon emissions.

Although no study is found in the existing literature that uses econometric method to investigate the relationship between R&D investment and energy and carbon intensities, several studies consider technological development into their empirical model to explore the impact on energy consumption and carbon emissions. For example, Tang and Tan (2013), by considering patent as an indicator for technological innovation, examine the influence of technological development on the consumption of electricity use in Malaysia. Employing time series data between 1970 and 2009 in the context of the autoregressive distributed lag (ARDL) approach, the study identifies that technological development assists to reduce electricity consumption considerably by improving energy efficiency. The study also indicates that technological development Granger-causes consumption of electricity in Malaysia. Thus, these findings imply that the Malaysian government should invest more in technological advancement to improve energy efficiency. Considering New Zealand and Norway as case studies, Fei et al. (2014) examine the relationship among technological progress, renewable energy and $CO_2$ emissions during 1971— 2010. The study also uses the patents number as an indicator for technological progress and findings reveal that technological advancement promotes renewable energy deployment and carbon emissions reduction in the case studies implying that R&D investment leads to promote clean energy use.

Fei and Rasiah (2014) explore the influence of electricity use on GDP growth by considering technological progress and prices for energy in their empirical model. Based on various econometric method including the ARDL model, the study fails to show that technological progress has any significant impact in reducing electricity use generated from fossil fuel. Sohag et al. (2015) find different empirical evidence in Malaysia between the period of 1985 and 2012. Employing the demand framework advocated by Marshall, the study indicates that technological development has significant influence on increasing energy efficiency as well as reducing energy consumption. Recently, Lee and Min (2015) investigate the relationship between eco-innovation and $CO_2$ emissions reductions in manufacturing firms of Japan. Using data during 2001— 2010, the authors report that eco-innovation helps to reduce carbon emissions significantly. Finally, Ahmed et al. (2016) examine the causal relationship between technological progress, biomass use, and $CO_2$ emissions in 24 European nations and reveal that technological progress has a substantial impact on minimising $CO_2$ emissions.

The above review of the existing studies suggests that a few studies are available on the relationship among technological development, energy consumption and $CO_2$ emissions at macro-level, however, these studies have limitations in providing direct policy recommendations in lessening $CO_2$ emissions. However, no study is found that mainly investigates the role of corporate R&D in reducing intensities of energy and $CO_2$ emissions.

Therefore, this study is undertaken to meet this existing research gap and, by contributing to the academic literature, and guidelines for policymakers by examining the following two hypotheses:

*H1: Corporate R&D decreases energy intensity significantly at firm level in G-6 countries.*

*H2: Corporate R&D decreases carbon emissions intensity significantly at firm level in G-6 countries.*

# 3 Research Design

## 3.1 Sample

The data for this study is obtained from two sources: energy and carbon emissions intensities and accounting data are collected from Bloomberg, whereas country-level data are sourced from World Development Indicators. The initial sample consists of panel data for G-6 countries indexed firms covering a period of 13 years (2004–2016), that allows the study to fully exploit the variations in carbon emissions and energy performance in response to R&D investment.[2] The sample includes the major industrial countries, which are major R&D investors and part of the Paris agreement to improve the environment. Disregarding the differences in industries, we initially selected 53,316 firm-year observations, which provide information on carbon emissions, energy consumption intensity, and R&D investment variables. Consistent with the prior literature, we require that these firms have essential carbon emissions intensity, energy consumption intensity, and accounting data to be part of the final sample. We also require each country to have at least 100 firm-year observations. Therefore, finally, we received 9,792 firm-years of data on 1,350 firms[3] for G-6 countries. We winsorize our variables at the 1st and 99th percentiles.

[2]Canada MSCI index, France CAC all shares index, Germany DAX index, Japan (Standard and Poor) S&P 1,000 index, UK FTSE 350 index, and US S&P 1,000 index firms.
3 Our analysis is based on the firms which have R&D data available.

## 3.2 Dependent variables

Table 1 provides the variables definitions while Table 2 presents the summary statistics. We measure the energy consumption intensity *(Energy_intensity_sale)* as total energy consumption scaled by sales turnover that shows 410.368 mean value. We measure the carbon emissions intensity *(CO_intensity_sale)* as total carbon emissions scaled by sales turnover in a year. We use such a measure because of its representation of the actual carbon emissions during production processes. The average carbon emissions intensity per sale is 222.873 (tons) in our pooled sample (see, Table 2). We scale both variables by sales to minimise the problem of heterogeneity (Lee et al., 2015).

[Insert Table 1 here]

## 3.3 Independent and control variables

The variable of interest in this study is R&D investment measured as total R&D investment in a firm during a given year scaled by sales turnover. Our sample shows the 3.061 mean value of *R&D_sale*. *GFCD* variable represents a significant event in the 2008–2010: the global financial crises (GFC). The GFC was triggered by sub-prime mortgages and bankruptcy of major financial institutions in the US that also affected the global economy during the period. In particular, the GFC mounted the uncertainty and investment risk by slowing down the economic growth. This negative impact of the GFC on firm R&D investment through bearish equity market and uncertainty resulting in lower sales volume is captured by the dummy variable. Except for the *GFCD*, the descriptive statistics of all variables are summarised in Table 2. The first two rows of the table are reserved for dependent variables. We measure return on assets *(ROA)* as net income scaled by total assets that depict the average value of 4.426. Leverage *(Lev)* is measured as total liabilities in a given year scaled by total assets and shows an average of 0.177. The relationship between energy and carbon emissions intensities and leverage is predicted to be positive in the eyes of the fund providers because the firm's clean environmental practices result in more sustainable firms. We also measure the insider ownership as a percentage of shares held by insiders *(%insider_OWN)* that has 1.688 mean value. Insider ownership may influence the investment in R&D projects. Capital intensity *(Capital_intens)* is measured by total sales revenue scaled by total assets that have an average value of 3.147. Size of firm, measured as the natural logarithm of total assets *(LN_Asset)*, depicts an average value of 4.809. The firm characteristics also include growth opportunities measured by a market-based indicator of the market-to-book ratio *(MTB)* with an average of 2.424, as in Table 2.

[Insert Tables 2 and 3 about here]

Table 3 panels A, B, and C, present the sample distribution by year, by GICS (Global Industrial Classification Standards), and by country. Panel A shows the distribution of firm-years across the sample period. Panel B shows the firm-years classification in different industry sectors where GICS 20 leads the sample with 22.07% of observations. Panel C illustrates the country-wise distribution of the sample. Japan has more firm-year observations followed by the US.

### 3.4 Correlation analysis

Table 4 presents the Pearson correlation matrix to test the multicollinearity among independent and dependent variables. The correlation among variables *R&D_sale, Energy_intensity_sale,* and *CO_intensity_sale* is negative which strengthens our hypotheses that R&D investment decreases energy intensity and carbon emissions intensity. The correlation among other variables is not higher than 0.50. Hence, multicollinearity is not a problem in our model. Also, to test the potential effect of multicollinearity, we calculate the variance inflation factor (VIF).[4] All the variables have a VIF less than 1.25, and the overall mean value is 1.08[5]. This suggests that multicollinearity is not an issue in the model.

[Insert Table 4 about here]

### 3.5 Model and estimation method

To examine the effect of R&D investment on energy intensity and carbon emissions intensity, we use the following model to test our hypotheses:

$$Y_{it} = \alpha + \beta_1 (R\&D\_sale)_{it} + \beta_2 (GFCD)_{it} + \delta_3 (firm\_controls)_{it} + \delta_4 \sum (Industry\ effects)_i + \delta_5 \sum (Year\ effects)_t + \delta_6 \sum (Country\ effects)_t + \varepsilon_{it} \qquad (1)$$

where $Y_{it}$ represents the outcome variables which are either energy intensity or carbon emissions intensity. Energy intensity is used to examine the H1, and carbon emissions intensity is used to investigate the H2. Our main independent variable is R&D investment *(R&D_sale)* in both hypotheses. R&D investment variable captures the firm's expenses on R&D, including green R&D and expenditures on improving/creating the new technologies to reduce the environmental emissions. A firm's investment in environmental performance can also be influenced by other factors. To minimise any estimation bias due to omitted variables, therefore, we include control variables following previous study (Lee et al., 2015). For example, capital intensity, size of firm, return on assets, level of debt, insider ownership, and market growth opportunities.

Prior studies commonly employ ordinary least square (OLS) regression controlling for year and industry effects. We use the OLS as baseline regression, controlling for industry (GICS) and year effects. The industry effect is expected to capture the effect of time-varying at industry level on energy intensity and carbon emissions. For example, changes in yearly

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[4]We do not report VIF results for the sake of brevity. The test results can be made available upon request.
[5]Lardaro (1993) suggests that multicollinearity can cause an issue if VIF exceeds 10.

outputs at industry level caused by business cycle can affect the firm's environmental performance. The magnitude of this effect is a function of the change in energy and carbon emissions intensity when industry output changes. Therefore, we need to control for this unobserved effect by including the industry variables. Otherwise, the estimated coefficients are subject to omitted variables bias. In a similar vein, changes in the level of industry output may affect the R&D investment. Hence, the estimated coefficients obtained from the variations are within an industry in a given year. Thus, a year-industry is expected to control for the effect of industry-level and time-varying fixed effects in an estimation of our model. To account for differences in country-level environmental policies, we include country fixed effects in our regressions. Further, to choose between the fixed effect and random effect, we perform a Hausman test in which the un-tabulated results confirm the suitability of the fixed effect (FE) that helps eliminate the omitted variable bias and controls for year fluctuations.[6] Additionally, we use one-year lagged R&D investment replacing the contemporaneous variables. The rationale behind this specification is that R&D investment requires time to influence the energy consumption intensity and carbon emission intensity. The standard errors were corrected for clustering of residuals at firm level to control for heteroscedasticity (Petersen, 2009).

## 3.6 Identification

Our independent variable R&D investment *(R&D_sale)* may face critique on potential endogeneity bias that arises due to forced investment in improving and creating new technologies in response to regulatory pressure (e.g., the Paris agreement) that leads to better environmental performance. Another reason may be that a shortage of funds affected by business cycle leads to poor environmental performance or other country-level factors may come in to play affecting our results. Therefore, our independent variable *(R&D_sale)* may

[6]The technique is commonly suggested for panel data estimation (see Wooldridge, 2002 for detail). FE was supported with large panel and extended time (see Wooldridge, 2002), which is the case of our study with $n$ = 1350 and $t$ = 13.

suffer from a bias and may not be systematically associated with our dependent variables *(Energy_intensity_sale and CO_intensity_sale)*. To the extent that linearity assumption of our regression analysis is violated, the prior model may result in a spurious estimation. To address this concern, we use three strategies including the addition of country-level variables in our model, propensity score matching (PSM) estimator, and an instrumental variable (IV) approach (Harford et al., 2012).

First, we employ the country-level variables following prior studies (see, Pinkowitz et al., 2006; Acharya et al., 2011) to address the concern that our findings are not driven by omitted variables problem. We add country-level variables namely GDP growth, government effectiveness, regulatory quality and corruption control index as additional variables in our regression *(Ln_gdp, Govt_effectivenss, Req_quality, and Corruption_con).*

Second, we use propensity score matching estimator (PSM) (e.g., Rosenbaum and Rubin, 1983; Lennox et al., 2013) to test the change in our dependent variables as a result of R&D investment. We implement the propensity score matching in two steps. In the first step, we run a logistic regression for *R&D_dummy* (a dummy variable equals one if there is R&D investment and zero otherwise) with other explanatory variables based on the treatment (with R&D) and the control (without R&D) groups. In the second step, we use the propensity scores to form one-to-one matched pairs for *R&D_dummy* and resultant difference in the energy intensity and carbon emissions (i.e., *Energy_intensity_sale, CO_intensity_sale)* may be attributed to differences in R&D investment rather than to other factors. We discuss the uniformity of firm-year observations in the identification section.

Third, we employ the instrumental variables (IV) (following de Villiers et al., 2011) to address the endogenous relationship between R&D investment and outcome variables (energy intensity and carbon emissions intensity). We estimate the regression model using two-stage least squares (2SLS) by incorporating IV. The IV regression first performed by regressing each endogenous variable (e.g., our test variables) on known determinants of R&D investment to obtain suitable instruments. These determinants include *ROA*, *GFCD*, *Lev*, among others. In the second stage, the modified version of Eq. (1) has the right-hand side endogenous variable replaced by the fitted value from the first-stage regression.

# 4 Results and Discussion

## 4.1 Energy intensity and R&D investment

Table 5 shows the results of the effect of R&D investment on energy intensity. Panel A shows the OLS specification results (columns 1–3) without control variables, without and with industry, year, country effects, and using FE (column 4), respectively. R&D investment has a negative impact on energy intensity that is significant at the 1% level suggesting that higher R&D investment improves (coefficient = -32.077) the energy efficiency.[7] We include industry, year and country effects with clustered standard errors at firm level in all the regression specifications, and *t-statistics* are reported below the coefficients in the parentheses.

Our results suggest that R&D investment *(R&D_sale)* has a significantly negative impact on the energy intensity and remain statistically similar even after controlling for firm-specific control variables, industry/year/country effects (coefficient = -28.617) and to use of FE regression. Notably, the significantly negative impact of R&D investment on energy intensity leads to energy efficiency. For instance, one percent increase in R&D investment leads to a decrease in energy intensity of 197.130 MW. The economic significance is also important. An increase in *R&D_sale* by one (sample) standard deviation (i.e., using Table 2) decreases the energy consumption per sale by approximately 0.36% [*R&D_sale* 4.659× (-32.077) /

[7]We also use the absolute values of the dependent variable and our results (un-tabulated) are consistent to those reported in Table 5.

*Energy_intensity_sale* (410.368) = -0.364]. Overall, these findings support our hypothesis H1 that states that R&D investment significantly decreases energy intensity.

Further, to test robustness, we re-define our dependent variable *Energy_intensity_sale* as energy intensity per asset *(Energy_intensity_asset).* We re-estimate our model using re-defined variable and report results in Panel B in Table 5 without control variables, without and with industry, year and country effects, and using FE regression, respectively. We find that *R&D_sale* has a significantly negative relationship with energy intensity per asset *(Energy_intensity_asset)* qualitatively same as in Panel A. Our results are consistent with the model and statistically significant at the 5% or better level across the columns 5–8. Our results once more support H1.

[Insert Table 5 about here]

## 4.2 Carbon emissions intensity and R&D investment

Table 6 shows the results of the effect of R&D investment on carbon emissions intensity. Panel A, column 1 shows the OLS results without control variables but including the industry, year and country effects. However, column 2 shows the results after controlling for firm-specific variables without industry, year and country effects, column 3 shows the same regression with industry, year and country effects, and column 4 shows the results in FE specification. R&D investment has a negative impact on carbon emissions intensity that is significant at the 1% level across all the columns. We cluster the standard errors at the firm level in all the regression specifications, and *t-statistics* are reported below the coefficients in the parentheses.

Our results suggest that R&D investment *(R&D_sale)* has a significant (at the 1% level) negative (coefficient = -10.239) impact on the carbon emissions intensity and remains quantitatively similar (coefficient = -7.915, significance at the 1% level) even after controlling for industry/year/country effects.[8] For instance, one percent increase in R&D investment leads to a decrease in carbon emissions of 10.239 tons, significant at the 1% level (column 1). Similarly, leverage (*Lev)* also positively affects the carbon emissions. The economic significance is also important. For instance, an increase in *R&D_sale* by one (sample) standard deviation (i.e., using Table 2) decreases the carbon emissions per sale by approximately 0.21% (tons) [*R&D_sale* 4.659× (-10.239) / *CO_intensity_sale* (222.873) = -0.214]. Overall, these findings support our H2 that states that R&D investment significantly decreases the carbon emissions intensity.

Further, as a robustness check, we re-define our dependent variable carbon emissions as carbon emissions intensity per asset *(CO_intensity_asset).* We re-estimate our model 1 replacing the re-defined variable and report results in Panel B in Table 6 (columns 5–8) without firm-specific control variables, without and with industry, year and country effects, and using FE, respectively. We find that *R&D_sale* has a significantly negative relationship with carbon emissions intensity per asset *(CO_intensity_asset)* similar to our main findings. Our results are consistent and statistically significant at the 1% or better level (coefficients = -5.922, -3.462 in columns 5 and 8, respectively). Our results once more support the H2.

[Insert Table 6 about here]

## 4.3 Identification

Our independent variable R&D investment *(R&D_sale)* may face an endogeneity bias due to investment in improving and creating environmentally friendly technology in response to regulatory pressure. Table 7 presents the results of three strategies including the addition of country-level variables, propensity score matching (PSM), and an instrumental variable (IV) approach 2SLS (Harford et al., 2012).

[8]We also use the absolute values of the dependent variable and our results (un-tabulated) are consistent to those reported in Table 5.

First, to avoid a potential omitted variables bias, we employ country-level variables, e.g., GDP growth, government effectiveness, regulatory quality, and corruption controls following prior studies (e.g., Pinkowitz et al., 2006; Acharya et al., 2011). We follow Pinkowitz et al. (2006) and include GDP growth as control variable as a proxy for economic development. Acharya et al. (2011) argue that different countries may have different R&D investment level depending on the economic development. Also, R&D investment may vary due to higher/lower economic development. Our next country-level variable is government effectiveness and regulatory quality. We use such variables because prior studies argue about the different levels of government controls in different countries leading to different environmental investment strategies and regulations. We also include corruption control index, which measures the level of corruption in a country. Highly corrupted countries lead to higher pay off to officials. Thus, firms may not need to invest in environmental performance in meeting statutory regulations. The government effectiveness, regulatory quality, and corruption controls are indexed variables ranging from -2.50 (weakest) to 2.50 (strongest). We report the results in Table 7 columns 1 and 2. Our results are qualitatively similar, as in Tables 5 and 6, even after controlling for country-level variables. Regulatory control negatively affects the energy and carbon emissions intensities.

Second, using the two-step propensity score matching (PSM) (e.g., Rosenbaum and Rubin, 1983; Lennox et al., 2013), we test the change in energy and carbon emissions intensities as a result of R&D investment. In the first step, we run a logistic regression on *RD_dummy* (a dummy variable equals one if there is R&D investment and zero otherwise) with other explanatory variables based on the treatment (with R&D) and the control (without R&D) groups. The predicted estimates are used as the propensity scores for each firm-year observation. In the second step, we use the propensity scores to form one-to-one matched pairs for *(RD_dummy).* We are able to effectively match 6,292 (*Energy_intensity_sale*) and 6,464

(*CO_intensity_sale*) firm-year observations for R&D dummy variable *(RD_dummy).* After such matching, our treatment and control groups are nearly indistinguishable along all independent variables except one, i.e., *R&D_sale*. As such, any difference in the energy and carbon emissions intensity (i.e., *Energy_intensity_sale and CO_intensity_sale)* may be attributed to differences in R&D investment rather than to explanatory variables.

[Insert Table 7 here]

We report results in Table 7 (columns 3 and 4) based on our matched firm-year observations. We find that *R&D_sale* significantly affect (at the 1% level) energy and carbon emissions intensities. These findings suggest that an increase in environmental performance (energy and carbon emissions intensities) is attributable to the systematic difference in R&D investment.

Third, we employ the instrumental variables (IV) approach following prior studies (e.g., de Villiers et al., 2011; Haque, 2017) to address the endogenous relationship between R&D investment and outcome variables. A valid instrument must satisfy two conditions. First, the relevance condition which requires that after controlling for the set of variables in our model, the IV should correlate with R&D investment. Second, the exclusion restriction which requires that conditioning on the full set of control variables, the IV influences energy consumption intensity and carbon emissions intensity only through its correlation with R&D investment. The IV regression first performed by regressing each endogenous variable (e.g., our test variables) on known determinants of R&D investment to obtain suitable instruments. These determinants include *Ln_Asset*, *ROA*, *GFCD*, *lev*, *Capital_intens*, *%insider_OWN*, and MTB. The first stage regressions, where endogenous variables are the dependent, produce significant and negative results (not reported), suggesting the validity of IVs. Moreover, the *p-value* of the Cragg-Donald F weak-instrument test is less than 0.05 for all the regressions, rejecting the null hypothesis that the instruments are weak. Also, Hansen's *J* instrument test (Davidson and

MacKinnon, 1993) examines if the IVs meet the exogeneity requirement. Hansen's *J* produces an insignificant *J* statistic (not shown), indicating that the IVs are valid. In the second stage, the modified version of Eq. (1) has the right-hand side endogenous variable replaced by the fitted value from the first-stage regression. We report results in columns 5 and 6 in Table 7. The second stage shows the statistically similar findings as in Tables 5 and 6. Thus, after minimising endogeneity concerns, we can safely infer that R&D investment reduces the energy and carbon emissions intensity.

### 4.4 Additional analysis

Our findings in the previous sections are based on a full sample. However, a higher number of firm-year observations in the sample are contributed by Japan, UK, and the US may concern our results. We re-run our model based on the sample excluding these countries and report results (columns 1 and 2) in Panel A in Table 8. These findings are statistically and economically similar to our main findings. Further, our sample includes firms from all industries, however, one may argue that financial and real estate firms are not detrimental to environment compared with other industries. To address this concern, we re-run our model excluding the firm-years from financial and real estate firms. Our results in columns 3 and 4 are consistent with main findings.

Additionally, we employ one-year lagged R&D investment to examine the dynamic effect on energy and carbon emissions intensities. The rationale behind this is that investment in R&D requires time to influence the firm environmental performance. We report results in Table 8 (columns 5 and 6) which indicate that corporate R&D investment improves energy efficiency and reduces carbon emissions consistent with our main findings.

Moreover, we employ alternative proxies for R&D investment in our regression model. First, we replace the R&D investment in our model with total R&D investment *(Ln_R&D)*.

Second, we replace R&D investment with R&D investment scaled by total assets. The similar specification has been used in Chen et al. (2015). Panel B in Table 8 reports results, which are largely identical to earlier estimates.

Furthermore, our sample covers several countries (6), and there is a possibility of high variation in R&D investment among these countries, which may cause a significant degree of heteroscedasticity. To address this concern, we implement the weighted least square (WLS) regression following prior study (e.g., Chen et al., 2015). The weight is the inverse of the within-country variance of the R&D investment. We report results of WLS in Panel B in Table 8. The coefficients remain statistically the same as in Tables 5 and 6, suggesting the robustness of our main findings to the potential high heteroscedasticity problem. We include all the control variables as specified in the model along with the year and industry effects in the regression specifications.

[Insert Table 8 about here]

# 5 Conclusions and Future Research Direction

Recently, raising energy efficiency and reducing carbon emissions have become top strategies within corporate environmental performance. Under the Paris Climate conference, corporate managers face regulatory pressure to increase energy efficiency and reduce carbon emissions by promoting innovations and technological advancement. In this connection, corporate R&D plays a substantial role since it assists in accomplishing technological development that increases production speed without the demand for increased energy. Moreover, it promotes the new and improved clean energy technologies which play a central role in the transition towards cleaner energy sources. When considering the significant impact of corporate R&D on firm’s environmental performance, this study extends the existing literature on firm environmental performance by providing the first empirical evidence on the effect of corporate R&D investment on energy and carbon emissions intensities in G-6 countries.

Our findings indicate that R&D investment has a significant negative impact on energy consumption and carbon emissions intensities. Our results further support the R&D investment including alternative proxies of energy and carbon emissions intensities. In a more comprehensive robustness analysis, using country-level variables, propensity score matching (PSM), and two-stage least squares; we further document the negative impact of R&D investment on environmental performance. Our findings are also robust to alternative econometric specifications, alternative variable specifications, and sub-samples. The findings of our study support the fundamental argument of the natural resource-based view that the employment of firm's resources and capabilities on environmental activities helps a firm to achieve sustainable competitiveness by reducing energy uses and carbon emissions. Moreover, the findings of our study have significant policy implications for business managers, policymakers, and regulators since it provides the empirical evidence on the importance of R&D investment in improving energy efficiency and reducing the carbon emissions.

There are a few limitations in our study that the readers should consider when they interpret the results. These limitations also lead to future research directions. First, in this study, we have used two proxies: energy intensity and carbon intensity to measure firm environmental performance. Although energy efficiency and carbon emissions represent two important domains of firm environmental performance, future research may extend the analysis to other specific dimensions of corporate environmental sustainability. Second, our study considers G-6 countries which are developed countries. Future studies may investigate this issue in the context of developing countries since the business environment and level of R&D investment (at firm level) is significantly different from developed countries to developing nations. Finally, although this study is one of the pioneer studies that investigate the role of R&D on energy consumption and carbon emissions, future studies can be more specific and investigate the impact of environmental R&D on firm's environmental performance once the data becomes available for G-6 countries.

Table 1. Variables definitions

| Notation | Variable name | Measure |
| --- | --- | --- |
| **Panel A: Dependent variable** | | |
| Energy_intensity_sale | Energy intensity per sales | Measured as total energy consumption scaled by total sales |
| CO_intensity_sale | Carbon emission intensity per sales | Measured as total carbon emission scaled by total sales |
| **Panel B: Independent and control variables** | | |
| R&D_sale | Research and development | Firm total investment in research and development scaled by sales revenue |
| GFCD | Global Financial crises dummy | A dummy variable equals 1if for 2008-2010 and 0 otherwise |
| Lev | Leverage | Firm total liabilities scaled by total assets |
| %insider_OWN | Insider ownership | Percentage of shares held by executives |
| Capital_intens | Capital intensity | Total assets scaled by total sales |
| LN_Asset | Firm size | Natural log of total assets |
| MTB | Market-to-book ratio | Calculated as market value equity plus book value of assets minus book value of equity divided by book value of assets. |

Table 2. Descriptive statistics

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Energy_intensity_sale | 9792 | 410.368 | 1206.485 | 0.099 | 8027.464 |
| CO_intensity_sale | 9792 | 222.873 | 754.194 | 0.024 | 5478.464 |
| R&D_sale | 9792 | 3.061 | 4.659658 | 1.000 | 23.081 |
| ROA | 9792 | 4.426 | 5.457002 | -13.529 | 23.394 |
| Lev | 9792 | 0.177 | 0.143833 | 0.000 | 0.631 |
| %insider_OWN | 9792 | 1.688 | 5.451366 | 0.000 | 40.576 |
| Capital_intens | 9792 | 3.147 | 6.290788 | 0.348 | 41.418 |
| LN_Asset | 9792 | 4.809 | 1.065722 | 2.585 | 7.236 |
| MTB | 9792 | 2.424 | 2.761613 | 0.388 | 19.000 |

Table 2 presents the descriptive statistics on full sample. Refer Table 1 for variables definitions.

Table 3. Sample

| Panel A | | | Panel B | | | Panel C | | |
|---|---|---|---|---|---|---|---|---|
| Firm year distribution | | | Sample industry composition | | | Country composition | | |
| Year | N | % of FY | GICS Sector | # of firms | % of sample | Country | N | % of FY |
| 2004 | 20 | 0.2 | 10 | 61 | 4.52 | US | 2,388 | 24.39 |
| 2005 | 170 | 1.74 | 15 | 155 | 11.48 | Japan | 4,147 | 42.35 |
| 2006 | 476 | 4.86 | 20 | 298 | 22.07 | UK | 1,873 | 19.13 |
| 2007 | 763 | 7.79 | 25 | 220 | 16.3 | Germany | 268 | 2.74 |
| 2008 | 860 | 8.78 | 30 | 114 | 8.44 | Canada | 376 | 3.84 |
| 2009 | 879 | 8.98 | 35 | 89 | 6.59 | France | 740 | 7.56 |
| 2010 | 932 | 9.52 | 40 | 128 | 9.48 | Total | 9,792 | 100 |
| 2011 | 992 | 10.13 | 45 | 149 | 11.03 | | | |
| 2012 | 1,056 | 10.78 | 50 | 15 | 1.11 | | | |
| 2013 | 1,164 | 11.89 | 55 | 61 | 4.51 | | | |
| 2014 | 1,190 | 12.15 | 60 | 60 | 4.44 | | | |
| 2015 | 1,138 | 11.62 | Total | 1350 | 100 | | | |
| 2016 | 152 | 1.55 | | | | | | |
| Total | 9,792 | 100 | | | | | | |

Table 3 describes the firm year distribution in Panel A. Panel B shows the sample industry composition and Panel C illustrates the country composition of sample.

Table 4. Correlation matrix

| Sr. No. | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | CO_intensity_sale | 1.000 | | | | | | | | | |
| 2 | Energy_intensity_sale | **0.184** | 1.000 | | | | | | | | |
| 3 | R&D_sale | **-0.147** | **-0.172** | 1.000 | | | | | | | |
| 4 | GFCD | -0.006 | -0.013 | 0.001 | 1.000 | | | | | | |
| 5 | ROA | -0.041 | **-0.015** | **0.131** | **0.027** | 1.000 | | | | | |
| 6 | Lev | **0.219** | **0.229** | **-0.144** | **-0.039** | **-0.087** | 1.000 | | | | |
| 7 | %insider_OWN | **0.131** | **0.050** | **-0.010** | **-0.009** | **0.044** | 0.055 | 1.000 | | | |
| 8 | Capital_intens | **0.062** | **0.044** | **0.050** | -0.007 | **-0.093** | -0.005 | 0.000 | 1.000 | | |
| 9 | LN_Asset | **-0.234** | **-0.267** | **0.036** | **0.026** | **-0.281** | **-0.311** | **-0.181** | 0.004 | 1.000 | |
| 10 | MTB | 0.013 | **0.024** | **0.068** | **-0.056** | **0.429** | **0.350** | **0.041** | **-0.003** | **-0.385** | 1.000 |

Table 4 shows the correlation between independent and dependent variables. Bold figures denote significant correlation at the 1% and 5% levels of significance.

Table 5. Regression of R&D investment and energy intensity

| | Panel A | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Variables | Energy_intensity_sales | | | | Energy_intensity_asset | | | |
| R&D_sale | -32.077*** | -32.961*** | -28.617*** | -15.060*** | -210.812*** | -25.566** | -163.323*** | -40.904** |
| | (-9.04) | (-8.63) | (-6.50) | (-2.93) | (-3.98) | (-2.18) | (-2.74) | (-2.16) |
| GFCD | - | -22.196 | 55.031 | 14.625 | - | 890.646* | 858.998 | 1085.645** |
| | - | (-0.44) | (0.40) | (1.39) | - | (1.91) | (0.46) | (2.11) |
| ROA | - | -1.886* | -8.595** | -5.612*** | - | 30.064* | 6.303* | -19.103 |
| | - | (-1.85) | (-2.27) | (-4.45) | - | (1.91) | (1.82) | (-0.31) |
| Lev | - | 1526.778*** | 73.580 | 103.248 | - | 1431.052 | 1523.902 | -2435.933 |
| | - | (9.98) | (0.51) | (1.24) | - | (0.81) | (0.79) | (-0.60) |
| %insider_OWN | - | -0.652* | 10.298*** | -19.525*** | - | -31.310 | -30.703 | -19.168 |
| | - | (-1.95) | (2.63) | (-6.05) | - | (-0.60) | (-0.58) | (-0.12) |
| Capital_intens | - | 25.071*** | -1.193 | 66.709*** | - | -41.049* | -45.273 | -630.158 |
| | - | (3.34) | (-0.13) | (5.87) | - | (-1.97) | (-0.37) | (-1.13) |
| LN_Asset | - | -316.802*** | 23.484 | -12.934 | - | -439.568* | -328.841 | 6345.182** |
| | - | (-14.93) | (0.79) | (-0.23) | - | (-1.78) | (-0.82) | (2.34) |
| MTB | - | -54.742*** | -35.340*** | -5.569* | - | -128.837* | -152.366* | 42.864 |
| | - | (-6.90) | (-4.90) | (-1.70) | - | (-1.90) | (-1.86) | (0.27) |
| Industry effect | Y | N | Y | | Y | N | Y | |
| Year effect | Y | N | Y | Y | Y | N | Y | Y |
| Country effect | Y | N | Y | Y | Y | N | Y | Y |
| Constant | -185.823** | 1913.956*** | 423.770** | 593.142** | -243.285*** | 2475.435* | 312.690** | -412.323*** |
| | (-4.09) | (15.27) | (2.21) | (2.23) | (3.08) | (1.70) | (2.16) | (-2.11) |
| N | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 |
| adj. R-sq | 0.250 | 0.128 | 0.361 | 0.152 | 0.048 | 0.132 | 0.131 | 0.261 |

This table presents the regression results of R&D investment on energy intensity. Panel A show the effect of R&D investment on energy intensity per sales without firm-specific control variables, without and with industry/year/country effect, and using FE regression, respectively. Panel B shows the effect of R&D investment on energy intensity per asset without firm-specific control variables, without and with industry/year/country effects, using FE regression, respectively. Robust standard error of each coefficient is shown in the parentheses. Standardised beta coefficients are reported at the 1%, 5% and 10% levels of significance with ***, **, * respectively.

Table 6. Regressions of R&D and carbon emission intensity

| | Panel A | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Variables | CO_intensity_sale | | | | CO_intensity_asset | | | |
| R&D_sale | -10.239*** | -10.802*** | -7.915*** | -6.528*** | -5.922*** | -7.861** | -3.171** | -3.462** |
| | (-6.80) | (-6.54) | (-4.24) | (-3.48) | (-2.78) | (-2.13) | (-2.15) | (-2.26) |
| GFCD | - | 6.197 | -15.495 | 5.366 | - | -24.347 | 2.209 | 1.210 |
| | - | (0.29) | (-0.30) | (1.44) | - | (-0.51) | (0.02) | (0.22) |
| ROA | - | -1.581* | -2.958* | -2.751*** | - | 4.552 | 2.476 | 0.869 |
| | - | (-1.92) | (-1.96) | (-6.41) | - | (1.19) | (0.63) | (1.38) |
| Lev | - | 857.172*** | 182.824*** | 45.807 | - | 412.217*** | 75.501** | 13.960 |
| | - | (14.06) | (3.16) | (1.59) | - | (3.02) | (2.45) | (1.33) |
| %insider_OWN | - | -0.673* | -4.131*** | -7.578*** | - | -2.879 | -0.011 | -5.016*** |
| | - | (-1.88) | (-3.36) | (-9.90) | - | (-0.92) | (-0.00) | (-4.47) |
| Capital_intens | - | 13.130*** | 6.819** | 12.232*** | - | -2.648 | -8.786 | -1.524 |
| | - | (4.55) | (2.19) | (4.72) | - | (-0.41) | (-1.08) | (-0.40) |
| LN_Asset | - | -93.823*** | -25.101** | -107.197*** | - | -91.749*** | -81.132*** | -171.106*** |
| | - | (-11.42) | (-2.09) | (-6.14) | - | (-4.99) | (-4.86) | (-6.68) |
| MTB | - | -22.645*** | -10.321*** | -0.873 | - | -14.661** | -11.381 | 1.350 |
| | - | (-7.37) | (-3.77) | (-0.81) | - | (-2.13) | (-1.60) | (0.86) |
| Industry effect | Y | N | Y | | Y | N | Y | |
| Year effect | Y | N | Y | Y | Y | N | Y | Y |
| Country effect | Y | N | Y | Y | Y | N | Y | Y |
| Constant | 539.294*** | 536.367*** | 181.166** | 797.075*** | 388.176** | 554.377*** | 152.959*** | 1021.999*** |
| | (3.21) | (11.18) | (2.17) | (9.31) | (2.14) | (5.16) | (3.21) | (8.13) |
| N | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 | 9792 |
| adj. R-sq | 0.236 | 0.097 | 0.342 | 0.179 | 0.146 | 0.081 | 0.183 | 0.233 |

This table presents the regression results of R&D investment effect on carbon emissions intensity. Panel A shows the effect of R&D investment on carbon emissions intensity per sales without firm-specific control variables, without and with industry/year/country effects, and using FE regression, respectively. Panel B shows the effect of R&D investment on carbon emissions intensity per asset without firm-specific control variables, without and with industry/year/country effects, and using FE regression, respectively. The robust standard error of each coefficient is shown in the parentheses. Standardised beta coefficients are reported at the 1%, 5% and 10% levels of significance with ***, **, * respectively.

Table 7. Identification

| | CL | | PSM | | 2SLS | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | Energy_intensity_sales | CO_intensity_sale | Energy_intensity_sales | CO_intensity_sale | Energy_intensity_sales | CO_intensity_sale |
| R&D_sale | -28.779*** | -7.123*** | -18.354*** | -5.002*** | -35.102*** | -9.118*** |
| | (-5.12) | (-3.13) | (-6.57) | (-3.64) | (-2.59) | (-2.86) |
| GFCD | 120.432 | 8.101 | 42.129 | 8.404 | 47.541 | -10.112 |
| | (0.99) | (1.21) | (0.44) | (0.46) | (1.63) | (-1.20) |
| ROA | -7.142** | -3.933** | 4.556 | 2.842** | -4.126 | -3.324* |
| | (-2.03) | (-2.09) | (1.57) | (2.13) | (-1.11) | (-1.82) |
| Lev | 62.121 | 179.123*** | 345.615*** | 289.635*** | 123.012* | 110.023*** |
| | (0.73) | (3.01) | (3.30) | (5.89) | (1.89) | (3.42) |
| %insider_OWN | 11.123*** | 4.123*** | 10.737*** | 1.697 | -17.384 | -3.934 |
| | (2.42) | (3.12) | (3.02) | (1.33) | (-1.13) | (-1.54) |
| Capital_intens | -1.149 | 6.280** | 2.906 | 9.274*** | 11.601 | 2.411 |
| | (-1.11) | (2.12) | (0.81) | (5.89) | (1.21) | (1.69) |
| LN_Asset | 20.141 | -23.230** | -61.261*** | -101.251*** | -116.140* | -112.912*** |
| | (0.83) | (-2.02) | (-2.91) | (-10.28) | (-1.88) | (-3.12) |
| MTB | -35.548*** | -10.023*** | -53.873*** | -20.314*** | -23.120 | -12.152 |
| | (-3.13) | (-2.92) | (-9.45) | (-7.99) | (-1.23) | (-1.33) |
| Corruption_con | 552.132 | 272.123** | | | | |
| | (1.42) | (2.01) | | | | |
| Govt_effectiveness | 70.699 | 60.253 | | | | |
| | (0.21) | (1.56) | | | | |
| Req_quality | -189.375* | -18.232* | | | | |
| | (-1.90) | (-1.89) | | | | |
| Ln_gdp | 734.123 | 373.823*** | | | | |
| | (1.76) | (2.52) | | | | |
| Industry effect | Y | Y | Y | Y | Y | Y |
| Year effect | Y | Y | Y | Y | Y | Y |
| Country effect | Y | Y | Y | Y | | |
| Constant | -234.323*** | 456.352*** | 856.060*** | 361.627*** | 222.172*** | 103.232*** |
| | (-2.77) | (-4.14) | (3.91) | (4.40) | (2.81) | (3.81) |
| N | 9792 | 9792 | 6292 | 6464 | 9792 | 9792 |
| adj. R-sq | 0.361 | 0.341 | 0.461 | 0.566 | 0.142 | 0.241 |

This table presents the results of robustness tests. Column 1 shows the effect of R&D investment on energy intensity per sale and column 2 shows the effect on carbon emissions intensity per sale after controlling for industry/year/country effects and country level variables. Columns 3 and 4 show the effect of R&D investment on energy intensity and carbon emissions intensity, respectively using propensity score matching estimators. Columns 5 and 6 show the relationship using 2SLS respectively. The industry, year, and country effects are included in all the regressions. Robust standard error of each coefficient is shown in the parentheses. Standardised beta coefficients are reported at the 1%, 5% and 10% levels of significance with ***, **, * respectively.

Table 8. Additional analysis

| Panel A | Excluding Japan, UK, US | | Excluding financial, real estate | | Lagged R&D | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | Energy_intensity_sales | CO_intensity_sale | Energy_intensity_sales | CO_intensity_sale | Energy_intensity_sales | CO_intensity_sale |
| R&D_sale | -76.208*** | -27.748*** | -33.950*** | -11.497*** | -25.133*** | -7.411*** |
| | (-4.40) | (-3.53) | (-9.02) | (-6.92) | (-5.95) | (-4.20) |
| GFCD | 418.565 | 353.617* | 178.421 | 74.575 | -4.865 | 4.087 |
| | (1.00) | (1.81) | (1.16) | (1.26) | (-0.11) | (0.22) |
| ROA | -26.628* | -8.303 | -10.925*** | -4.150** | -7.324* | -2.695* |
| | (-1.74) | (-1.18) | (-2.59) | (-2.41) | (-1.95) | (-1.81) |
| Lev | 398.362** | 635.364*** | 685.437*** | 591.576*** | 57.699* | 167.357*** |
| | (2.40) | (6.29) | (4.34) | (9.21) | (1.90) | (2.96) |
| %insider_OWN | -9.854 | 10.950** | 3.160 | 1.833 | 5.963* | 4.399*** |
| | (-0.89) | (2.37) | (0.72) | (1.31) | (1.84) | (3.61) |
| Capital_intens | -14.785 | 10.889 | -12.460 | 3.868 | -8.769* | 3.322 |
| | (-0.86) | (1.34) | (-1.64) | (1.28) | (-1.90) | (1.21) |
| LN_Asset | 29.349 | -207.481*** | 25.267 | -0.855 | 30.592 | -21.560* |
| | (0.23) | (-3.60) | (0.79) | (-0.06) | (1.04) | (-1.82) |
| MTB | -87.770* | -84.202*** | -63.394*** | -23.205*** | -34.577*** | -10.350*** |
| | (-1.78) | (-3.71) | (-8.08) | (-7.52) | (-4.88) | (-3.88) |
| Industry effect | Y | Y | Y | Y | Y | Y |
| Year effect | Y | Y | Y | Y | Y | Y |
| Country effect | Y | Y | Y | Y | Y | Y |
| Constant | 1066.674** | 1342.323*** | 1325.905*** | 384.421*** | 573.178*** | 202.628** |
| | (2.15) | (3.98) | (5.65) | (4.24) | (2.63) | (2.38) |
| N | 1384 | 1384 | 8333 | 8333 | 8592 | 8592 |
| adj. R-sq | 0.115 | 0.181 | 0.189 | 0.130 | 0.357 | 0.361 |

| Panel B | | |
|---|---|---|
| | (1) | (2) |
| Variables | Energy_intensity_sales | CO_intensity_sale |
| R&D | -310.267** | -137.920*** |
| | (-4.59) | (-4.63) |
| R&D_asset | -31.114*** | -11.198*** |
| | (-2.83) | (-2.32) |
| WLS | -591.349*** | -232.688*** |
| | (-5.15) | (-4.25) |
| Other controls | Y | Y |
| Industry effect | Y | Y |
| Year effect | Y | Y |
| Country effect | Y | Y |

This table presents the results of additional analysis. Panel A column 1 shows the effect of R&D investment on energy intensity per sale and column 2 shows the effect on carbon emissions intensity per sale in a sample of excluding Japan, UK, and the US. Columns 3 and 4 show the effect of R&D investment on energy intensity and carbon emissions intensity in a sample excluding financial and real estate firms, respectively. Columns

5 and 6 show the lagged effect of R&D investment. Panel B shows the results with alternative variables and alternative approach (WLS). Robust standard error of each coefficient is shown in the parentheses. Standardised beta coefficients are reported at the 1%, 5% and 10% levels of significance with ***, **, * respectively.

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